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CONVOLUTIONAL NEURAL NETWORK APPLICATION IN VOLCANIC TREMOR IDENTIFICATION DURING THE 2008-2009 PRE-ERUPTIVE EPISODE OF MT. SEMERU, INDONESIA

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ABSTRACT: A convolutional neural network model has been constructed to detect volcanic tremor signals of Mt. Semeru during the years 2008 to 2009. This model was trained without first providing any discriminating features. The training data consists of 600 events, including 300 volcanic tremors and 300 non-tremors. The data augmentation process produced a total of 4800 data points, with 2400 volcanic tremor and 2400 non-volcanic tremor events. The resulting model has a training and validation accuracy rate of 99.51% and 96.93%, respectively. This model has successfully detected volcanic tremor signals in a mixed dataset of 14 seismograms. This leads to the conclusion that supervised machine learning can be further utilized in volcanic activity monitoring systems.

Keywords: convolutional neural network, machine learning, volcanic tremor, Mt. Semeru

1. Introduction

Volcanic tremor is continuous seismic activity produced by active volcanoes, with emergent or impulsive onsets, making it nearly impossible to pinpoint the event's start. This characteristic differentiates volcanic tremor from volcanic earthquakes, since the latter have a clear first arrival. The frequency content of volcanic tremor usually consists of a series of peaks in the 0.1-7.0 Hz band. Several observations indicate that volcanic tremor may occur prior to or after an eruption, with durations ranging from several minutes to months. Hence, volcanic tremor has attracted considerable attention from seismologists because of its potential value as a tool for forecasting eruptions [1]. Comparison of waveforms and frequency contents between volcanic tremor and earthquake is indicated in Fig. 1.

Mt. Semeru is one of the active volcanoes in East Java, Indonesia, where volcanic tremors were often detected and extensively studied. The frequency of these volcanic tremors ranges from 1.00 Hz to 2.96 Hz [2]. Oftentimes, volcanic tremors recorded by seismic stations surrounding Mt. Semeru are dominated by their fundamental frequency and its harmonics, which are commonly known as harmonic tremors. Based on their possible source mechanisms, harmonic tremors are classified into three types: isolated harmonic tremors, harmonic tremors prior to volcanic eruptions, and harmonic tremors after volcanic eruptions. The frequency contents of harmonic tremors from Mount Semeru range from 1.14 Hz to 2.50 Hz. Other than that, Mt. Semeru is also known to generate spasmodic tremors, which are characterised by irregular waveforms and spectral peaks. This type of volcanic tremor usually occurs after volcanic eruptions. The dominant frequencies of spasmodic tremors from Mt. Semeru range from 1.56 Hz to 1.86 Hz [3].

Despite their usefulness in forecasting an impending eruption, detecting volcanic tremors quickly and manually is difficult and time-consuming. On the other hand, rapid detection of volcanic tremors will provide useful information on the volcanic early warning system. Therefore, the help of a computer algorithm that is able to recognize and differentiate volcanic tremor among other volcanic activities is required. Supervised machine learning algorithm AdaBoost has been successfully utilized to detect seismic signals of volcanic tremor and lahar based on their dominant and centroid frequencies, as well as their permutation entropy in Mt. Redoubt. This algorithm works well despite using only three discriminating features [4], whereas accurate volcanic signal classification requires a large number of features.

Previous studies suggest that machine learning performs well at classifying seismic events from active volcanoes. Classification based on feature selection for seismic events generated by the Cotopaxi Volcano has been explored in both the time and frequency domains [5], focusing on classifying event types: long period (LP), volcanic tremor (VT), and Hybrid (HB), with successful results for LP and VT classifications. In another study, the continuous wavelet transform (CWT) for spectral analysis of volcano-seismic activity of Santiaguito Volcano in Guatemala was also utilized [6]. The use of multiple machine learning algorithms, such as recurrent neural networks (RNNs), long short-term memory (LSTM), and gated recurrent units (GRUs), to detect and classify continuous volcanic seismic events at Antarctica's Deception Island Volcano has also led to satisfactory results [7]. Spectrogram cross-correlations with a K-nearest neighbour algorithm were performed to classify five types of volcanic events at Llaima Volcano in Chile, achieving an accuracy of 95% [8]. Lastly, a Bayesian neural network was applied to classify five event classes across two volcanoes, achieving 92.1% accuracy across combined datasets and demonstrating that their uncertainties corresponded to the volcanoes' states of unrest [9].

Considering the aforementioned success in machine learning applications for seismic event classification of active volcanoes, we performed volcanic tremor signal detection using supervised machine learning, specifically a Convolutional Neural Network (CNN). The primary advantage of CNNs over earlier models is their ability to automatically identify important features without human intervention, which has led to their widespread adoption. CNNs have also been applied to tackle complex visual tasks that require substantial computation and are primarily used for image classification, segmentation, object detection, video processing, natural language processing, and speech recognition [10,11]. CNN has been utilised in volcano-seismology data processing, such as to discriminate tectonic and volcano-related seismic signals [12]. CNNs have also been applied to volcano-related seismic signals, particularly for classifying spectral images of long-period (LP) and volcano-tectonic (VT) events, as well as other types of seismic signals produced by active volcanoes [13,14], as shown in Figure 1.

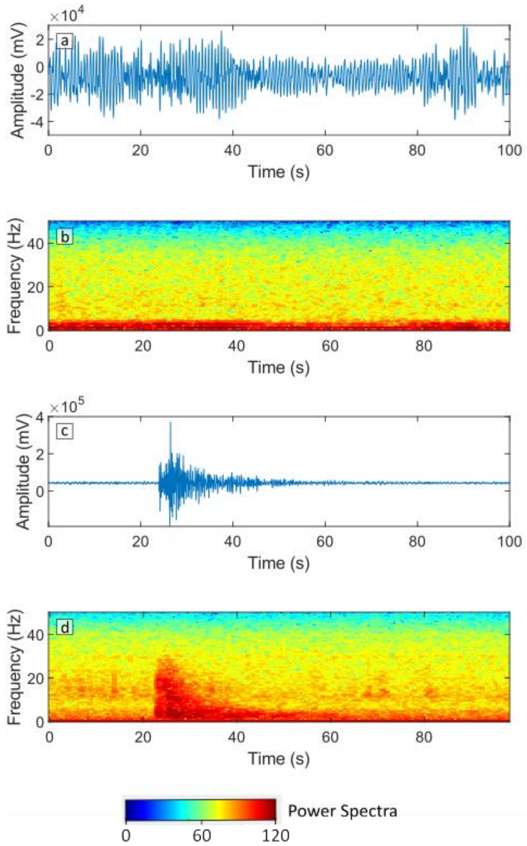

Figure 1 Comparison of seismic waveforms and frequency contents of volcanic tremors (a and b) and eruption (c and d) recorded by one of the monitoring seismic stations, LKR, in Mt. Semeru.

2. Data

Volcanic activity of Mt. Semeru is monitored by stations equipped with short-period vertical seismometers such as the Mark Product L4-C (1 Hz). The seismic signals are then transmitted via telemetry to the Mt. Sawur Observation Office, recorded on both analogue drum recorders (Kinemetrics PS-2) and digital data loggers (Hakusan Datamark LS-7000).

Given that the feature extraction is image-based and focuses on tremor spectrograms, we chose CNN as the most suitable algorithm for the task. This study aims to construct a CNN model capable of precisely detecting volcanic tremor signals using pre-classified data, without defining discriminating features prior to training. Then validated the model's performance by using it to predict pre-classified volcanic tremor signals included in its training data.

Since November 2005, the Centre for Volcanology and Geological Hazard Mitigation (CVGHM), in collaboration with the Sakurajima Volcano Research Centre (SVRC), has installed a broadband seismometer (STS-2, Streckeisen), a water-tube tiltmeter, and a biaxial tiltmeter at the summit area, 0.7 km northeast of the Jonggring Seloko crater [15]. In total, Mt. Semeru is monitored by 5 seismic stations, namely Puncak (PCK), Kepolo (KPL), Tretes (TRS), Leker (LKR), and Besuk Bang (BSB). The locations of each monitoring station are presented in Figure 2.

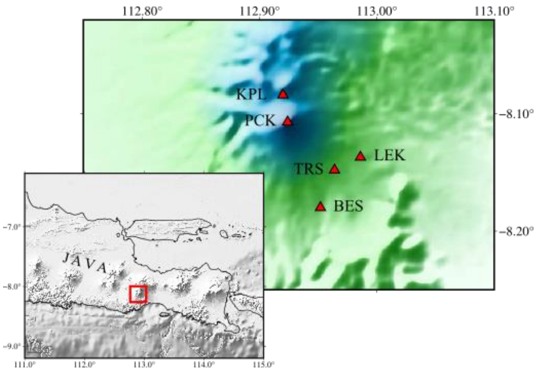

Figure 2 Monitoring stations of Mt. Semeru.

The data utilized in this research consist of seismic data originating from Mt. Semeru from 2008 to 2009, prior to its eruptive stage in 2010. We then compile seismic signals containing waveforms recorded by stations LKR, TRS, and BES. These waveforms were then cut for each event and manually classified into two categories: volcanic tremor and non-tremor events. The pre-dataset consists of seismograms with a duration of twenty seconds. There are 600 events in this pre-dataset, including 300 volcanic tremors and 300 non- tremors.

The volcanic tremor data that we included in this work were handpicked and carefully reviewed. It is important to note that we only included events that clearly resemble volcanic tremor when converted to the frequency domain. By doing so, we ensure that volcanic tremor can be captured indisputably. The small number of events included in our pre-dataset should not be a problem since more data does not always guarantee better results. On the other hand, poor-quality or irrelevant data can actually degrade classification performance instead [16].

3. Methods

To create a larger dataset, a 20-s moving window that slides in 5-s increments was used to split each event into shorter waveforms. These shorter waveforms will be referred to as samples from here on. It is important to note that, unlike any other volcanic or volcano-tectonic events, volcanic tremor does not have apparent onsets. Hence, even after being sliced into shorter waveforms, the characteristics of volcanic tremors are still recognizable in each sample. Each of these samples was then augmented by flipping and low-pass filtering with cut-off frequencies of 10 Hz, 15 Hz, and 20 Hz, increasing the number of samples by eightfold when including the original and the flipped-original samples (Figure 3). Short-time Fourier Transform (STFT) was used to obtain spectrograms from both original and augmented samples. The resulting spectrograms were added to our dataset array. This process was repeated until the end of the last event in the original dataset. Finally, the dataset was saved as a JSON file. The entire data augmentation process is shown in Figure 4.

The data augmentation process produced quite different samples compared to the original ones. From the resulting seismograms, observed that the unique volcanic tremor characteristics of Mt. Semeru are commonly observed at 2 to 5 Hz. Therefore, using a cut-off frequency for our low-pass filter does not eliminate the frequency band we actually need; it only removes the noise. The augmentation process produced a total of 4800 data points, divided into 2400 volcanic tremor and 2400 non-volcanic tremor events. Spectrograms were placed in a separate dataset, distinct from another dataset containing all the seismograms.

Both the seismogram and spectrogram datasets were then used to train the neural network model. We utilized a LeNet network to classify the dataset into tremor and non-tremor events since this model required minimal input from the user. The first stage was initialising the current and max epochs used in our CNN parameter training. The next stage was loading the seismic dataset from memory and dividing it into training (60%) and validation (40%) sets. The CNN parameters were trained using forward propagation and backpropagation. The training stages were carried out for the specified maximum epochs. The resulting artificial neural network model was then stored in memory. The machine learning algorithms in this study are built in Python using the open-source TensorFlow library.

This study used a trained CNN to predict tremor from 20-s seismograms. A spectrogram of each seismogram was obtained using the Short Time Fourier Transform (STFT) and later utilised in the forward propagation process to obtain predictive results. Similar to the previous training process, this predictive process is also constructed by using the Python programming language.

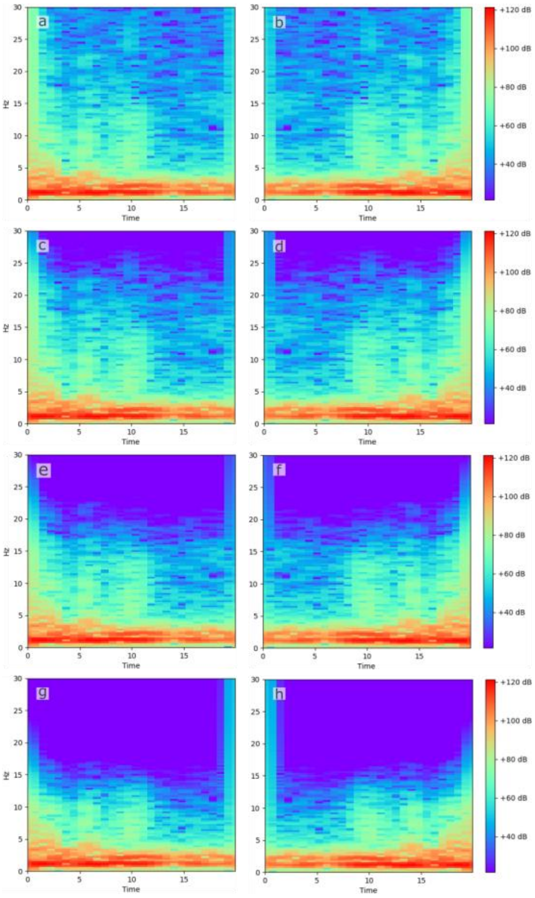

Figure 3 Augmented data for model training that consists of original and flipped spectrograms. (a) original spectrogram, (b) flipped original spectrogram, (c) low-pass filtered original spectrogram with 10 Hz cut-off frequency, (d) flipped seismogram c, (e) low-pass filtered original spectrogram with 15 Hz cut-off frequency, (f) flipped seismogram e, (g) low-pass filtered original spectrogram with 20 Hz cut-off frequency, and (h) flipped seismogram g.

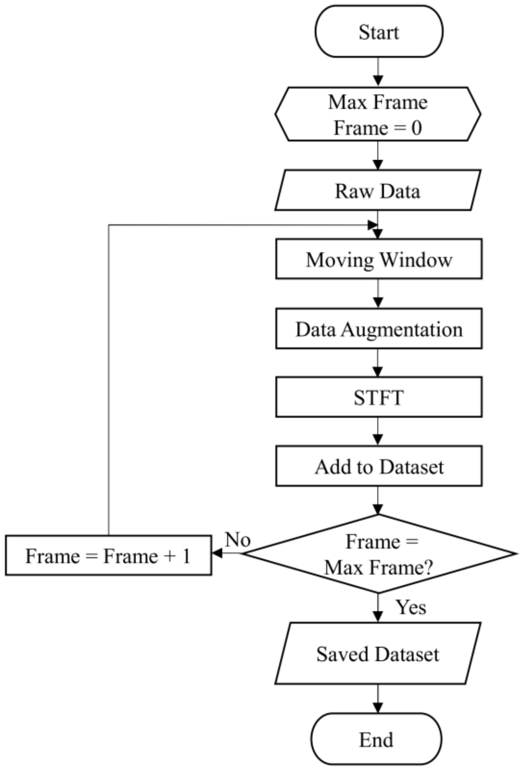

Figure 4 Flowchart depicting the steps taken during data preparation. The original dataset is augmented to obtain a larger dataset.

4. Results and Discussion

The CNN model trained for 10 epochs achieved a training accuracy of 99.41% and a validation accuracy of 95.63%, with training and validation losses of 0.0260 and 0.1221, respectively. These results indicate that the model effectively learned the classification task, although its validation performance was lower than that obtained with 20 epochs.

In the 15-epoch experiment, the model achieved a training accuracy of 99.37% and a validation accuracy of 95.47%, with training and validation losses of 0.0286 and 0.1317, respectively. Compared with the 10-epoch and 20-epoch experiments, this configuration showed slightly lower validation performance.

In the final run, training was conducted for 20 epochs, yielding a training accuracy of 99.51%, a training loss of 0.0216, a validation accuracy of 96.93%, and a validation loss of 0.1079. Compared with the 10-epoch and 15-epoch runs, this model yielded the highest validation accuracy and the lowest validation loss. The relatively small gap between training and validation accuracy (2.58%), together with the low loss values, suggests that the model achieved good generalization under the present experimental setting and did not exhibit severe underfitting or overfitting. Nevertheless, this interpretation is limited to the current train–validation split and should be further confirmed using a larger independent test set or cross-validation in future work. A comparison of accuracy and loss values across experiments is shown in Table 1. The overall process of our model training is indicated in Figure 5.

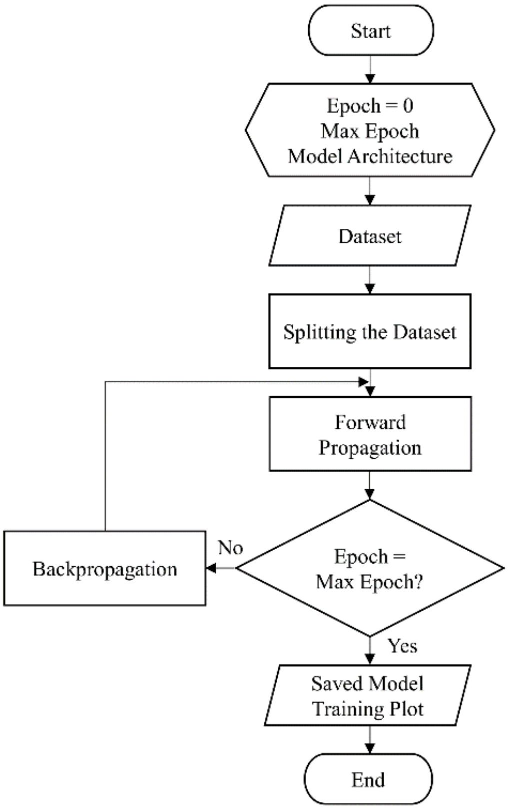

Figure 5 Flowchart of model training process.

The final model was then used to predict the classification of seismograms outside the dataset. The process of CNN detection using our model is shown in Figure 6. There are 14 data points, divided into 7 seismograms of volcanic tremor and 7 of non-volcanic tremor. The prediction results in this experiment are shown in Table 2.

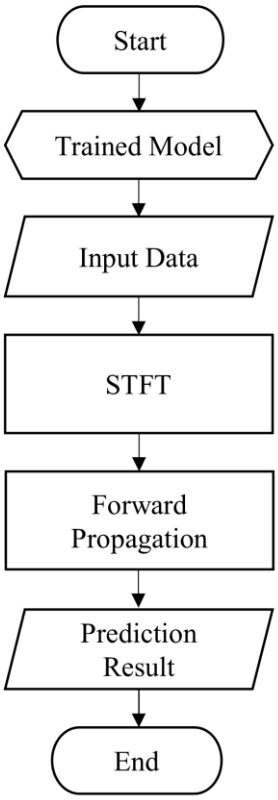

Figure 6 The whole process of volcanic tremor detection by using the resulting CNN model.

Table 1 A comparison of accuracy and loss values in each model training experiment

	Number of epochs	Training accuracy rate	Training loss
1	10	99.41%	0.0260
2	15	99.37%	0.0286
3	20	99.51%	0.0216
	Number of epochs	**Validation accuracy rate**	**Validation loss**
1	10	95.63%	0.1221
2	15	95.47%	0.1317
3	20	96.93%	0.1079

Table 2 The resulting CNN model prediction when introduced to a new dataset.

Condition	Prediction Result Non-VT	VT	Condition
Non-VT	99.73%	0.27%	Non-VT
Non-VT	99.87%	0.13%	Non-VT
Non-VT	99.98%	0.12%	Non-VT
Non-VT	99.98%	0.12%	Non-VT
Non-VT	99.99%	0.01%	Non-VT
Non-VT	96.92%	3.08%	Non-VT
Non-VT	99.99%	0.01%	Non-VT

Condition	Prediction Non-VT	Result VT	Condition
VT	0.43%	99.57%	VT
VT	0.01%	99.99%	VT
VT	0.04%	99.96%	VT
VT	0.01%	99.99%	VT
VT	0.01%	99.99%	VT
VT	0.05%	99.95%	VT
VT	0.01%	99.99%	VT

The prediction results in Table 2 indicate that our model can accurately detect volcanic tremor signals among a dataset containing 14 seismograms, of which 7 seismograms were non-tremor. This leads to the conclusion that supervised machine learning can be further utilized in volcanic activity monitoring systems.

To provide a more comprehensive evaluation of the classification performance, we additionally computed precision, recall, and F1-score for the final 20-epoch model using the external test dataset of 14 seismograms (7 volcanic tremors and 7 non-volcanic tremors). All samples were correctly classified, corresponding to a confusion matrix of TP = 7, TN = 7, FP = 0, and FN = 0 when volcanic tremor was treated as the positive class. Accordingly, the model achieved 100% precision, 100% recall, and 100% F1-score on this limited test set.

5. Conclusions

A Convolutional Neural Network model was developed to identify volcanic tremor signals of Mt. Semeru using seismic data from 2008 to 2009. Using 600 labelled events and an augmented dataset of 4,800 samples, the best-performing model achieved a training accuracy of 99.51% and a validation accuracy of 96.93%. On the external test dataset of 14 seismograms, the model achieved 100% accuracy, precision, recall, and F1-score. These findings suggest that CNN-based classification is promising for volcanic tremor identification in volcanic monitoring systems. However, because the external test set was small, further validation with a larger independent dataset is recommended.

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